difficult, the LPC is found for all stimuli, whether detected signals, undetected signals, or nonsignals. Although the subjects' detection rates remained quite good, they reported far greater concentration on and evaluation of each stimulus compared to an easy discrimination condition. Furthermore, we found that an easy discrimination in a go, no-go reaction time experiment results at first in LPC to both stimuli, whereas after the task has become routinized the LPC is absent. In this connection, Sokolov (*5*) has reported that when a subject is given the task of responding to one of two stimuli, and the discrimination between these stimuli is made very difficult, orienting responses persist to both stimuli for hundreds of trials. When the discrimination is easy, the orienting response begins to disappear once the required response becomes stabilized.

The presence of the LPC for unpredictable changes in stimulation when the subject is not attending to the stimuli (the usual paradigm for the orienting response) as well as for discrimination tasks in which the subject actively attends to the stimuli, suggests the operation of a neurophysiological mechanism common to both situations. Since the orienting response represents a relatively primitive capacity of organisms to respond selectively to changes in the environment, it is possible that the processes which underlie it may form the basis for more complex mechanisms of perceptual selectivity. In both situations stimulus information must continually be stored and compared with incoming stimuli. In the usual orienting situation (when stimuli match the template for information to be disregarded established by prior experience and the current needs of the organism), they are processed routinely and elicit no special notice (*13*). However, when an unexpected mismatch occurs, a shift of attention to the stimulus is elicited, and additional perceptual and cognitive mechanisms are called into play to evaluate the significance of the mismatch. Although no shift of attention is necessary in a discrimination task where the stimuli are actively attended, the determination of match or mismatch might still be made by the same comparator mechanism that operates in orienting responses. With a relatively easy discrimination, as in our main vigilance task, the comparator mechanism might suffice to call forth further evaluation of mismatches (the LPC thus being a correlate of the evaluative process) and failures to register mismatch would be associated with lack of evaluative (LPC) processes. Thus, the physiological processes underlying the LPC cannot represent activity of the comparator mechanism itself, since the LPC was absent for the nonsignals; nor can it be a correlate of conscious detection of a mismatch, since it is present for all stimuli, whether match or mismatch, in a difficult discrimination. In the latter situation, the comparator mechanism is apparently incapable of adequately differentiating the relevant stimuli, and cognitive processes for more complex evaluation are directed to all stimuli. When the stimuli to be discriminated alternate frequently, as in a go, no-go situation, ease of discrimination is associated with establishment of a reliable operation of the comparator mechanism, leading to routinization of response and eliminating the need for special evaluation (reflected in disappearance of the LPC).

The LPC, then, can be elicited in different situations; but whether it is elicited by conditions associated with orienting responses or when the subject is actively engaged in stimulus discrimination, the LPC appears to be a correlate of central processes for cognitive evaluation of stimulus significance.

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8. Photic stimuli were circles (5°), 10 msec in duration, presented to the left eye. Fixation was maintained on the center of a dim red cross.
9. Subjects sat in an electrostatically shielded, sound-attenuated booth positioned on a biteboard during photic stimulation and sitting unrestrained during auditory stimulation. The strain on the subject of remaining positioned on the biteboard, made it necessary to confine the visual condition to a period of about 25 minutes. The auditory condition lasted about 45 minutes. Electroencephalogram (amplifier band pass, 0.06 to 600 hz) was recorded on a frequency-modulated analog magnetic tape, summated with a modified Mnemotron CAT 400 and written out on a Mosley X-Y plotter.
10. Four subjects participated in the visual condition, two of whom were retained for the auditory condition.
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12. Davis (*11*) did report that one of six subjects had a 300-msec positive component for the AER to the comparison tone.
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14. Supported by grants ID-2TI-MH-6418, NB-03356, MH-06723, and k-K3-NB-31,816 from the U.S. Public Health Service.

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Gaussian Behavior of the Electroencephalogram: Changes during Performance of Mental Task

Abstract. *The probability distribution of the amplitude of scalp electroencephalogram has been investigated in an adult subject in the idle state, and during performance of a mental arithmetic task. Based on a large sample, the electroencephalogram in this subject in the idle state follows a Gaussian (normal) probability function 66 percent of the time. During performance of the arithmetic task, the portion of Gaussian electroencephalogram decreases to 32 percent. The probability function characterizing gross electroencephalographic activity is determined by the degree of mutual interaction of individual cellular generators of wave activity in the tissue underneath the recording electrode. The data imply an increase in the cooperative activity of cortical neuronal elements during performance of a mental task.*

After three decades of intensive investigation, the spontaneous electrical activity recorded from the brain [electroencephalogram (EEG)] still remains one of the most elusive aspects of cerebral function. It is best characterized as continuous wave activity of variable amplitude and frequency, with inconstant phase relations; its overall character is quite similar to random noise.

Arising spontaneously, the EEG is difficult to correlate in consistent manner with discrete behavioral events. Superposition and summation, which bring about dramatic improvement in signal-to-noise ratio in such time-locked events as evoked potentials, completely fail with regard to the EEG. Generally, when several EEG segments are superimposed, the algebraic sum tends to zero, in keeping with the "noise-like" character of this activity.

Nevertheless, the frequency spectrum of the EEG is not flat. The presence of dominant frequencies such as the alpha rhythm, often apparent even in visual inspection, has drawn attention to the frequency distribution of brain waves. Quantitative analysis of the EEG also has been concerned primarily with frequency aspects. Initially autocorrelation, and, more recently, spectral analysis have been extensively used to specify the frequency distribution of the EEG, and to provide information on the peaks present at various frequencies (*1*). These peaks have also been studied in controlled environment conditions and during task performance (*2*).

By contrast, the implications of the similarity of EEG and random noise have received only scant consideration, probably because of the conviction that there would not be any meaningful information to be found in brain waves if they were merely "noise." Indeed, to the communications engineer, noise implies only masking of information, or perhaps even its complete absence. Yet, while in communications noise chiefly originates from unstable components and transmission lines, little is known about the origins and mechanism of generation of noise-like activity in the brain. The possibility remains that, unlike man-made communications system in which noise is an encumbrance, the brain may use noise as a desirable or perhaps even essential factor.

One possible approach to the EEG is through study of its statistical properties; certain inferences may be made in this way about the basic mechanisms of generation of the EEG. A most important clue to the statistical character of the EEG derives from intracellular measurements of the subthreshold potential variations present in nerve cells in the cerebral cortex. Incessant oscillations of the membrane potential are found in cortical cells in the unanesthetized cat. If this subthreshold activity is viewed as a stationary, or time-invariant, statistical process (at least over relatively brief periods of time), then the probability distribution of this statistical process is obtainable directly from the histogram of instantaneous amplitude values of the recorded activity. To construct such a histogram, the entire amplitude range is divided into an arbitrary number of classes, the activity is sampled periodically, and a count is made of the number of samples falling in each amplitude class. In this manner an estimate is obtained of the relative frequency of different amplitude values; for a reasonable number of samples, this provides also an estimate of the probability distribution of the activity from which the samples have been derived.

In all cases studied with this technique, the probability distribution of intracellular potential oscillations has been non-Gaussian (*3*). In contrast, the gross EEG activity recorded at the same time from an adjacent site follows Gaussian probability distribution [(*4*); in the statistics this probability distribution is more commonly referred to as "normal"; here both terms will be used interchangeably].

There is little doubt that these relatively slow potential changes recorded from individual cortical neurons (*5*) contribute most significantly to gross EEG activity. If large groups of cortical neurons were oscillating in synchrony, gross activity would constitute a simple replica of the ongoing wave activity in individual neurons. Since the probability distribution of amplitude changes in the single cell is non-Gaussian, it might have been expected in these circumstances that the gross EEG also would be non-Gaussian. Thus the experimental observations on normal distribution of EEG amplitude provide an indication that the individual contributions of unitary generators cannot be fully synchronized (*6*). The simplest explanation compatible with these facts is that of complete statistical independence of unitary EEG generators (*7*); but such a view is rather difficult to accept on anatomical and physiological grounds when it is considered that a major contribution to intracellular wave activity undoubtedly derives from synaptic potentials. Since these potentials arise in consequence of impulse transmission in anatomical connections, and since connections of this nature are invariate (at least on the time scale involved here), absolute independence of the generators is rather unlikely. A physiologically more realistic model may be the one calling for a nonlinear relation between individual unitary generators; the transition from sub- to suprathreshold state of the generators may well provide the requisite nonlinearity (*8*).

In either model, the dissimilarity of probability distributions characterizing the EEG and individual nerve cells is an expression of the mutual asynchrony of unitary EEG generators. Other evidence for asynchrony was available from experiments with extracellular microelectrodes. Simultaneous recordings from two microelectrodes set 30 μ apart are quite different, indicating absence of synchrony even on this minute scale (*9*). However, these observations do not shed much light on the actual relation between individual generators. For this, simultaneous intracellular recordings from two adjacent cortical neurons must be obtained; the formidable technical difficulties involved have impeded so far the collection of such data.

Still, the view of the EEG as the sum of activities of asynchronous unitary generators makes possible certain predictions even in absence of knowledge of the precise relation of the generators. When the unitary generators are desynchronized the gross EEG should display Gaussian probability distribution of the amplitude; yet, when the relation between individual neurons is intensified, such as in sleep or certain behavioral situations, this probability distribution should be modified. I tested this hypothesis with regard to behavioral stimuli and now give a brief account of the differences found between Gaussian behavior of the EEG in the idle state and during performance of a mental task.

A normal adult was seated in a soundproof dark chamber and was not disturbed for about 20 minutes after attachment of scalp leads. At this stage, a record of the subject's idle EEG activity was taken without alerting him in any way. Then the mental task was explained verbally and assigned to the subject (mental calculation of the product 2^N for N as large as possible), but he did not complete the task until after an additional EEG record was obtained. Then a previously agreed-upon auditory signal to start calculation was

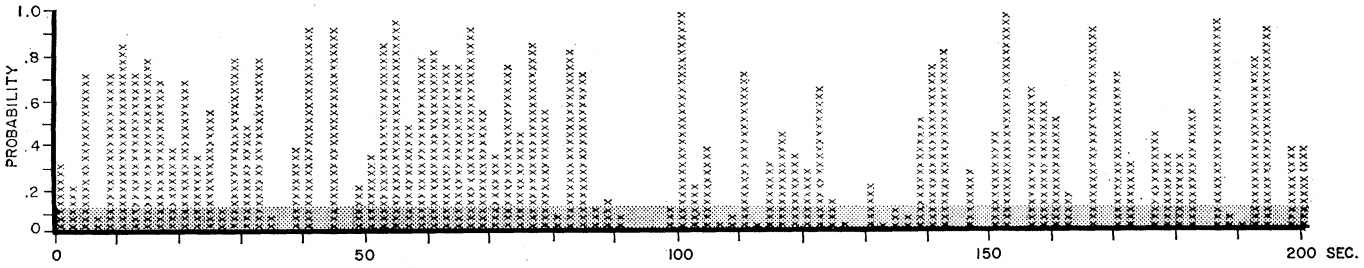

Fig. 1. Results of amplitude analysis of EEG in an idle subject. Each vertical line represents an EEG sample of 2 seconds' duration. There are altogether 101 such samples, derived from an EEG record 202 seconds long. The height of each vertical line indicates the likelihood that the same 2-second EEG record represents a sample drawn from a Gaussian population. The shaded area $(0 < P < .1)$ is below the rejection level; accordingly, lines which do not go above this area represent EEG samples which are not likely to be Gaussian.

delivered. A third EEG sample was obtained during performance of the task. The duration of each of the three EEG records was 4 to 5 minutes. Recording was bipolar, with a midline, fronto-occipital electrode configuration, with standard scalp leads of 10 to 15 kilohm; ground connection was established through a clip electrode on the left ear lobe. Amplifier bandpass was set at 0.3 to 70 cycle/sec.

Analog-to-digital conversion was performed on-line, at sampling rate of 200 per second. Amplitude histograms of the EEG were constructed with an IBM-7094 computer, with use of a special Fortran IV program. [After normalization of their area to unity, amplitude histograms are directly convertible to curves of the probability distribution function of the sample (*10*).] The mean and variance of the normalized curve were calculated, and a synthetic normal distribution characterized by the same mean and variance was subsequently constructed. The fit between the two curves was examined by means of χ^2 goodness-of-fit test (*11*, *12*). The main arbitrary element in this procedure is the duration of EEG sample contained in each histogram. Although it might appear that a larger sample should contribute to increase confidence, this is true only if the statistical properties of the data are homogenous throughout duration of the entire record (in other words, the data should exhibit stationarity in the wide sense). It has been observed that with data blocks lasting over 2 seconds, the effects of inherent nonstationarity of the EEG become increasingly serious, leading to erroneously low estimates of goodness-of-fit (*11–13*). In the experiment reported here, EEG records were divided into 2-second blocks. Blocks were individually analyzed, following the routine described above, and the likelihood that the block under test would constitute a sample drawn from a Gaussian population was found from the χ^2 test. Finally, a serial plot of the probability values found for consecutive data blocks was prepared by the computer (Fig. 1).

Results of analysis of an EEG record taken from the idle subject are presented in Fig. 1. In this plot, each 2-second data block is represented as a vertical line; the height of the line is proportional to the likelihood that the analyzed block derives from a Gaussian population, as given by the χ^2 test. It is customary in statistical usage to consider the test as positive (that is, accept the hypothesis that the sample belongs to a Gaussian population) whenever $P > .05$. When the test is made more rigorous, the significant level is set at $P = .10$. In the following, the significance level for acceptance was set at $P = .10$, and, whenever the dashed horizontal line denoting this level in Fig. 1 is reached or exceeded, the hypothesis may be accepted that the data block tested derives from a normal population.

Table 1. Summary of results obtained in three different behavioral situations by the χ^2 goodness-of-fit test. A series of consecutive EEG records, each 2 seconds long (400 samples), was tested for fit against the corresponding normal distributions (which possessed the same mean and variance as the EEG record under analysis); 100 records (200 seconds) were analyzed for an adult male in each behavioral situation. With the level for rejection set at $P = .1$, approximately 10 percent "false negatives" may be expected even if the entire population were Gaussian (*14*). Hence, the rejections (%) in each behavioral situation (column 2) do not reflect the genuine non-Gaussian epochs (%), which are found by subtracting 10 percent of the number of acceptable Gaussian records from the total number of rejections (column 3). This procedure, which provides correction for the statistical error type I (but not type II) yields the figures listed in column 2 of the table.

Condition	Rejections (%)	Rejections after correction (%)
Subject idle	40	≃ 34
Task assigned	70	≃ 67
Task executed	71	≃ 68

The probability values obtained in the χ^2 test varied widely from trial to trial (Fig. 1). This is a consequence of the nature of the χ^2 test, the results of which are only expressed in terms of probability; specifically, even when the hypothesis under test happens to be true (that is, the examined EEG block does constitute a sample from a normal population), the χ^2 figures obtained in the goodness-of-fit test are distributed according to the χ^2 distribution (*11*). Therefore even in cases where the hypothesis is confirmed, approximately 10 percent of the trials must fall below the critical probability $P = .10$ [the "type I error" of statistics, (*11*, *12*, *14*)]. Hence only failures in excess of 10 percent of the trials can be considered significant. The total number of failures is in excess of 10 percent (Table 1). Elsewhere the excess of failures in χ^2 test of the EEG in the idle state is further analyzed, and evidence is produced that while the EEG is distributed most of the time in Gaussian fashion, there are also brief periods of non-Gaussian, synchronized activity (*11*).

The effect of mental task on amplitude distribution of the EEG is a sharp increase in non-Gaussian activity (Table 1); the number of failures in the χ^2 test (in excess of the permissible 10 percent) is more than twice that in the idle state. The decline in Gaussian behavior takes place as soon as the subject is made aware of the test (Table 1, column 2). In the fronto-occipital lead configuration there is no significant difference between the waiting period after announcement of the test, and actual performance; a different picture is found with bilaterally symmetric lead configurations, in which the waiting period is similar to the idle EEG (*12*).

The use of 100 consecutive trials in each of the three behavioral situations provides substantial assurance against errors arising from inadequate population size. As concerns inherent statistical errors, the type I error ("false negatives") is fixed in all three situations, since it is solely determined by the significance level chosen; the type II error ["false positives" (*14*)] is likely to decrease as the percentage of failures goes up (*12*). Hence any possible error in Table 1 may only be in direction of underestimating the decline in Gaussian behavior induced by task performance.

Thus, amplitude analysis of the EEG may provide significant information on mental function. These results have since been confirmed with additional subjects, and with greater number of scalp leads (*12*). It has often been assumed that low-voltage, fast activity implies "desynchronized EEG," and high-voltage, slow activity is indicative of "synchronization." There may be some justification for this usage from a descriptive viewpoint, but microelectrode investigations apparently do not support the identification of "synchronized" and "desynchronized" EEG with corresponding changes on the neuronal level. Therefore, a particularly important feature of our amplitude analysis is the straightforward interpretation which may be made in terms of unitary neuronal synchronization and desynchronization. Although this interpretation still lacks direct experimental proof, it is difficult to conceive of any process apart from a change in relation of individual generators, which could bring about such marked increase in rejections in the χ^2 test (*11*). As with many other statistical tests, however, the results only apply to the population as a whole, and any mechanism which acts on the neuronal population (such as subcortical "pacemakers") is bound to affect the statistical interrelations of the neural elements contributing to the recorded surface EEG.

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6. In summation of synchronized generators, Gaussian activity would also ensue, provided that the probability functions of these generators would be identically normal. This cannot however be the case with the neuronal wave generators, as the probability distribution of those is non-Gaussian (see *3*).
7. This statement follows directly from the central limit theorem of statistics: the sum of a large number of independent variables (or generators) is distributed normally, regardless of the probability distribution of the individual variables, and provided only that they possess finite mean and variance.
8. R. Elul and W. R. Adey, *Nature* **212**, 1424 (1966).
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10. See, for example, H. Cramér, *The Elements of Probability Theory* (Wiley, New York, 1955), pp. 168–171.
11. R. Elul, in preparation.
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Attention Reduction and Suppressed Direct-Current Potentials in the Human Brain

Abstract. *Distraction suppresses direct-current potentials (contingent negative variation) recorded from the human scalp. This reduction is accompanied by retarded reaction time. Contingent negative variation and reaction time appear to reflect a common process, attention.*

Electrophysiological studies of normal mental processes are relatively incomplete. With the advent of computers, study of electrical brain activity and information processing has increased (*1*). Computer averaging techniques have been widely used in studies of averaged evoked potentials and attentional processes (*2*). Using such techniques, Walter discovered a reliable d-c potential in the human brain (*3*). This latter phenomenon, contingent negative variation, is an electronegative change in the frontal areas of the human brain which hinges on the association of two successively presented stimuli. A typical experimental situation generating contingent negative variation is that of reaction time. The first stimulus is a preparatory or warning stimulus; the second stimulus is one to which a motor response is required. For example, a light flash (first stimulus) followed in 1.5 seconds by a tone (second stimulus), which is terminated by a key press, gives rise within the interval between presentation of light and tone to a slowly ascending electronegative potential whose maximum of 20 to 30 μv occurs between 0.2 and 1.5 seconds and whose duration is normally terminated with the requisite motor response (Fig. 1). This wave is usually recorded with a scalp lead at the vertex (C_z), the mastoid being used for the reference electrode.

Early studies of contingent negative variation stressed its relation to "cortical priming" with particular emphasis on expectancy, defined as the relative subjective certainty that the first and second stimuli will occur (contingent negative variation was renamed the expectancy wave by Walter) (*4*) and on motivation level (*5*) and conation, or intention to act (*6*). Recently, however, Tecce (*2*) suggested that amplitude of contingent negative variation is primarily related to attention; but no systematic attempt has yet been made to show that attentional processes determine amplitude of contingent negative variation. Our experiment was designed to establish the relation of contingent negative variation and attention by demonstrating that distraction reduces amplitude of contingent negative variation. If the amplitude is